Sonar image processing for underwater object detection based on high resolution system

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Abstract—This paper is concerned with the problem of recognition of objects laying on the sea-bed and presented on sonar images. Considering that high resolution sonar system provides acoustic images of high-quality, several researches have been interested in Synthetic Aperture Sonar (SAS) and Sides can sonar images for underwater objects. This work presents recent detection algorithms targeting their main specificity and innovations during the different steps of sonar image processing.

Keywords-component; objects recognition; high-quality system; image processing; sonar image.

I. INTRODUCTION

Thanks to advances in digital electronics, many new sonar systems have appeared. Today we found out the acoustic camera, interferometric sonar, synthetic aperture sonar (SAS), the synthesis incoherent sonar, parametric sonar, Side scan sonar, etc [1]. Sonar image obtained from such sonar instruments are used in different fields to realize seafloor task, such as navigation, seabed mapping, fishing, ocean drilling barrier, oil exploration, mines' detection, and so on [2].

In view of the interest in the field of mining since hispanic times and nowadays, several research studies have been interested in the mining and have been developed for the detection of underwater mines using high-frequency system. Both sides can sonar and Synthetic Aperture Sonar (SAS) technologies provide high-resolution imagery for mine hunting application. As they are characterized by their very high performance resolution, images provided by SAS [4] and sides can sonar are of great interest for the detection and classification of objects lying on the seabed or buried in the sediment, and mainly, the underwater mines[3][5]. In the context of mine warfare, detected objects can be classified from their cast shadow or their high intensity reflection of the wave on the object. So several studies have been developed within this context and are differentiated by their approaches and methods used to obtain the search object within the sonar image. But for the reason of the complexity of oceanic environment and the particular optical properties of light in water, the sonar image obtained from sonar instrument is polluted by the noise. Therefore, it became an important research field to remove the noise of sonar image [10] before the application of various approaches of image processing. Furthermore, according to the operated approach, pre-or post-processing are generally used to make each step of processing more robust [10]. Thus, from the preprocessing to the classification process, recent approaches present certain variability that we will explain in this work still within the context of sonar image processing for the underwater objects detection using high frequency systems.

This paper is organized as follows. In Section II, various methods of pre-processing sonar images are represented. In Section III, the principle, the utility and the different recent approaches of sonar image textural analysis are cited. Finally, different segmentation and classification methods for underwater objects are represented in Section IV.

II. SONAR IMAGE PRE-PROCESSING METHODS

Because of the particular optical properties of light in water and the presence of suspended particles, sonar images are very noisy, the lighting is not uniform, the colors are muted and the contrast is low. Most methods dedicated to reduce the noise apply different filtering and are often classified in two categories: the methods acting in the spatial domain and those acting in the transformed domain. Stéphane Bazeille and Isabelle Quidu [6] proposed an algorithm for image preprocessing sonar which allows correction of lighting, noise and color and requires no user intervention or a priori information on the acquisition conditions. This algorithm is a combination of four different filters each of which aims to revise a special defect. To eliminate the defects of non-uniformity of illumination, the Homomorphic filtering is used. Sonar image is decomposed

into the reflectance factor and the illumination intensity [11] using the following equation:

$$g(x,y)=i(x,y).r(x,y). \tag{1}$$

g(x,y) is the sonar image, i(x, y) is the multiplication factor of illumination and r(x, y) is the reflectance function. Applied Homomorphic filtering algorithm is summed up in the following steps:

 Separation of the components of illumination and reflectance using the log of the image in (2):

$$g(x,y) = In(f(x,y)) = In(i(x,y).r(x,y)) = In(i(x,y)) + In(r(x,y)).$$
(2)

Evaluation of Fourier transform of the log-image.
 The resulting equation is as follows:

$$G(w_x, w_y) = I(w_x, w_y) + R(w_x, w_y). \tag{3}$$

• High-pass filtering of the Fourier transform: use of the H modified Gaussian filter :

$$G(w_x, w_y) = H(w_x, w_y).I(w_x, w_y) + H(w_x, w_y).R(w_x, w_y).$$
(4)

Where

$$H(w_{x}, w_{y}) = (r_{H} - r_{L}). (1 - w_{x} \exp\left(-\frac{w_{x}^{2} + w_{y}^{2}}{2*\delta_{w}^{2}}\right))) + r_{L}.$$
(5)

 r_H and r_L are the maximum and minimum coefficients of the filter and δ_x is the factor determining the cutoff frequency.

- Evaluations of inverse Fourier transform to return in the spatial domain.
- Application of the exponential function to get the filtered image.

The effects of the application of this algorithm on a sonar image captured by a SAS system are shown in Fig. 1.

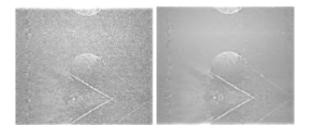


Figure 1. The effects of Homomorphic filtering on the preprocessing algorithm. In the right image, complete algorithm is applied, in the left image, the Homomorphic filtering is not used.

The filtering process is then based on Fourier transform and uses the 'H' modified Gaussian filter. On the other hand, in order to attenuate noise acquisition, wavelet transform is used. Indeed, various denoising methods act in the wavelets domain. These methods have three steps: the computation of a wavelet transform (WT), the filtering of the detail wavelet coefficients and the computation of the corresponding inverse WT (IWT) [7]. Fig. 2 shows the principle of the wavelet decomposition.

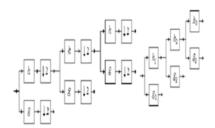


Figure 2. Wavelets transform (WT) implementation, hlowpass filter, g-highpass filter; h and g form a pair of quadarture mirror filters.

A first category of denoising methods applied in the wavelets domain is based on nonparametric techniques [18] and uses the hard or the soft thresholding filters. Stéphane Bazeille and Isabelle Quidu [6]'s algorithm of reducing noise acquisition is based on wavelet decomposition of the image corrupted by white Gaussian noise using A. F. Abdelmour and I. W. Selesnick's orthogonal wavelet [15]. In order to get an approximate value of the noise variance, Donoho and Johnstone's estimator is applied [18] using the following estimator σ_n :

$$\sigma_n^2 = \left(\frac{median(|y_i|)}{0.6745}\right)^2. \tag{6}$$

Where the y_i are the coefficients of diagonal details wavelet at the finest scale. Finally, to correct color mutation, the algorithm applied a linear translation of RGB three histograms so as to equalize their average.

Other algorithms are developed in the same context. The paper by Buades [20] proposed denoising algorithm acting in the spatial domain. The algorithm explained a very modern non parametric denoising method based on non-local (NL) averaging. The NL-means algorithm tries to take advantage of the high degree of redundancy of the sonar image and the value of pixel is estimated by the neighbors' pixel value using the following equation:

$$NL_{x}(i) = \sum_{j \in I} \beta(i,j)x(j). \tag{7}$$

For each pixel x_i , the weight $\beta(i,j)$ depends on the similarity between the pixels i and his neighbor i. And "I" defines the set of alls "i" neighbors. The paper by Katkovnik [16] discussed a denoising method for the case of additive noise in a transform's domain. The method proposed combined the local polynomial approximation (LPA) with the maximum likelihood and quasi likelihood for the design of nonlinear filters. Another excellent denoising method for the case of transform's domain makes the object of Argenti [12]. In their paper, algorithms proposed for noise reducing used for estimation either a maximum a posteriori (MAP) or a linear minimum mean square error (LMMSE) filtering approach [40]. The denoising procedure is based on estimating Non-Subsampled Contourlet Transfor (NSCT) coefficients of each band by calculating their fourth order moments. [40]

To validate the performance of each proposed denoising algorithm, a robust criterion must be specified to note the overall quality of the image. Such a criterion is not yet defined in the literature and is still the subject of several searches. The performance of the proposed algorithm is often evaluated by presenting the effect of pretreatment on the next steps of sonar image processing and especially segmentation.

III. SONAR IMAGES TEXTURAL ANALYSIS

The analysis of textured images plays an important role in image processing, pattern recognition and particularly in sonar images classification [8], [9], [13]. There are different methods of feature extraction for image processing cited in [21]. As part of mine detection, the distinction between the image of a mine and an object that physically resembles a mine is very complex and is relied on the recognition in shapes and textures. Ph. Blondel [14]'s study combined two different advances in sidescan sonar applications [30], [31]. In fact, sidescan sonar images in particular, are mainly described by their tonal and textural properties. This method of advanced image analysis has been developed and based on the quantification and recognition of acoustic textures. The method has been extensively calibrated and groundtruthed in complex terrains. The algorithm implicated was then successfully applied to the detection of mines. H. Laanaya's paper [22] presented a method of sonar image classification based on the process of extracting knowledge from data. In Previous Laayana's works [25], [26], [27] methods for the extraction of textural attributes in images upgrades gray are quite similar. The texture is early characterized as the statistics of the response to scale-space filters such as Gabor and wavelet analysis, co-occurrence matrix [33] or multifractal descriptors [34]. A co-occurrence matrix is a NG * NG size matrix where NG is the number of gray levels of the image. Haralick [35] defined 14 texture features from the co-occurrence matrix. In this work only six parameters are used: homogeneity, contrast, entropy, correlation, uniformity and directivity.

The homogeneity in the δ direction is given by:

$$HM = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} C_{\delta}^2 (i, j).$$
 (8)

 C_{δ} is the correlation matrix, whereas NG is the gray level's image.

The estimated contrast is given by:

$$CT = \frac{1}{N_G - 1} \sum_{k=0}^{N_G - 1} k^2 \sum_{i,j=1,|i-j|=k}^{N_G} C_{\delta}(i,j).$$
 (10)

The entropy in C_{δ} is defined by:

$$EN = 1 - \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} C_{\delta}(i, j) \log(C_{\delta}(i, j)).$$
 (11)

The correlation between the rows and columns of the matrix is given by:

$$CR = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} ((i - \mu_x)(j - \mu_y) C_{\delta}(i, j)) / (\sigma_x \sigma_y).$$
 (12)

where μ_x , σ_x , μ_y , σ_y represent respectively the averages and standard deviations of the marginal distributions of elements of co-occurrence matrix. The directivity defined the existence of a preferred direction of the texture and is computed by the following equation:

$$DR = \sum_{i=1}^{N_G} C_{\delta}(i, j). \tag{13}$$

The uniformity characterizes the proportion of the same gray level and is given by:

$$UN = \sum_{i=1}^{N_G} C_{\delta} (i, j)^2.$$
 (14)

Once these parameters are evaluated, the following parameters: energy, entropy and average are calculated in each sub-image of wavelets decomposition. Also, for the analysis of image texture, a Gabor filter bank (a set of filters, each selecting a frequency and a particular angle in the image) is applied. Those parameters extracted are thus transformed by linear (principal component analysis PCA, linear discriminant analysis DLA) or nonlinear (Curvilinear Component Analysis CCA) extracting methods and form discriminating parameters departure. K.Imen's papers [17] propose a new region-based segmentation of textured sonar images with respect to seafloor types. Haralick's parameters [35], coefficients of wavelet and Gabor are used as descriptors to characterize seabed. The contribution of this method is that the choice of descriptors is not randomly but based on techniques for selection of parameters and attributes of the most discriminating textures. The selection problem is addressed through the definition of a similarity measure adapted to the characteristics of relevant textures towards a learning set of textures. The (dis)-similarity between a seabed type T and T⁸ texture is calculated in (15) using the Kullback-Leibler divergence (KL) [41]:

$$KL_{w}^{(-)}(Q^{k}, P^{\theta}(T)) + \sum_{f=1}^{F} \sum_{i=1}^{J} w_{f}^{2} w_{\theta i \theta j} KL(Q_{f, i}^{k} P_{f}^{\theta}(T)).$$
 (15)

Once the proposed approach based on texture analysis gives the textural features, an application to sonar texture classification is addressed. Nevertheless, when the approach of detecting underwater objects is not based on texture features, the classification step is realized by exploring other paths of segmentation.

IV. SONAR IMAGE SEGMENTATION AND CLASSIFICATION METHODS

Different methods of segmentation and classification of underwater objects mainly a mine are cited in [19]. Many segmentation methods are based on statistical model using first and second order statistics [28], [29]. Frederic's work [23] presented a new method of underwater mine echoes detection. Segmentation echoes step is based at first on using local statistical proprieties of sonar images. Higher Order Statistics (HOS) are then used to improve detection tool [24]. The first and second order statistics have served to a mean-standard deviation representation. Kurtosis and Skewness are evaluated on a square window for each pixel [32] to obtain correct location of the echoes of detected objects. As a test of Frederic's algorithm, the case of sonar image presented in Fig. 3 is taken. Corresponding meanstandard deviation representation is presented in Fig. 4. In this figure we show the result of three tests realized in order to segment the test image using [23] the first and second image's local statistical proprieties. For each of three calculation window, the dashed line represents the proportionality coefficient between mean and standard deviation (estimated with the Weibull law), and the solid lines feature the threshold values.

On each calculation window, the expression of Skewness (16) and Kurtosis (17) is given as a function of the proportion of pixels in the deterministic calculation window (ρ) and the signal to noise ratio (p) as follows:

$$S_F(\rho, p) = \frac{p}{\sqrt{1-p}} \frac{(1-2p)\rho^3 - 3p}{(p\rho^2 + 1)^{\frac{3}{2}}}.$$
 (16)

$$K_F(\rho, p) = \frac{\frac{\rho}{1-p} \left((1 - 6p + 6p^2)\rho^4 - 6(1 - 2p)\rho^2 + 3 \right)}{(p\rho^2 + 1)^2}.$$
 (17)

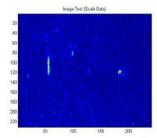


Figure 3. SAS test image of buried and proud objects at showing two types of mine: a spherical (placed in the left end of the image) and a second practically buried in the bottom (placed in the right end).

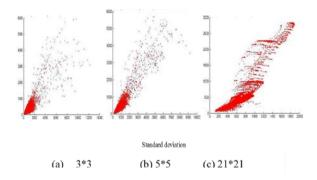


Figure 4. Mean–standard deviation representation of the test image. This representation is built with a 3 x 3 window size in figure (a), 5 x 5 in figure (b) and 21 x 21 in figure (c).

To automate the segmentation algorithm, the standard deviation threshold value is evaluated using the entropy criterion. The entropy value is calculated on each axis of the image using the Shannon formula as follows:

$$H_{axis} = -\sum_{i \in I} p_{axis}(i) log_2 \ p_{axis}(i). \tag{18}$$

Where $p_{axis}(i)$ is the number of segmented pixels in the column i (respectively line i), and "I" is the set of columns (respectively lines).

This method is finally tested on real SAS data containing underwater and other objects, laying on the seabed or buried on the seafloor [23].

The test of the segmentation method on the test SAS image and the value of entropy calculated for each axis using the above equation are presented in Fig. 5.

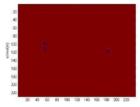


Figure 5. Segmentation graph and repartition of segmented pixels according to the two axes. Results for a standard deviation value = 8000 and an average = 6750. Computed entropies: X-axis: 4.16; Y-axis: 8.76.

Another view of classification approach is revealed in Arnaud Martin and I. Isabelle Quidu's paper [37]. In fact, for sonar images classification, A. Martin and I. Isabelle take advantage of Support vector machines (SVM) classifier based on the statistical learning theory [38]. The

contribution of the proposed method is the use of the belief functions theory for the combination of binary classifiers coming from the SVM. The modelization of the basic belief assignments is then evaluated directly from the decision functions given by the SVM. Additionally, the approach proposed in Laayana's paper [22] aims to make first robust traditional classification methods, such as support vector machines or k-nearest neighbors then apply evidential and fuzzy SVM for regression. For finding the SVM's hyper plane, the proposed method uses one of two approaches oneagainst-one or approach one-against-rest. The choice of the k nearest neighbors is labeled by a set distance. The individual are then placed in the class to which belongs the greatest K number of neighbors. Another proposed approach to integrate the concept of fuzzy in SVM is to model the noise on the inputs by weighting. For the evaluation of classification approaches exploited, [22] adopts the result of [36] work. The comparison between the different classifiers showed that SVM gives the best classification rate. Later Isabelle Leblond and Isabelle Quidu propose an original strategy to classify underwater objects from SAS images [39]. The method proposed in this work allows classifying an object from multiple views via a prediction of the new angle of visit for the additional views in order to take off the ambiguities on the classification. The classification algorithm is presented in Fig. 6 as a chain of transactions whose extent is based on the results of the previous step.

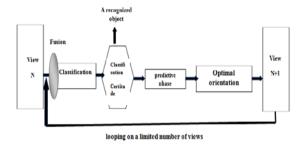


Figure 6. Simplified diagram of Isabelle Leblond and Isabelle Quidu' classification algorithm.

The first operation consists in the classification of the sonar image using the method of K-nearest neighbor applied to the result of the ACP presentation in the plane of the object. In case where an additional view must be chosen, the prediction step is performed. This primary step is to estimate the orientation of the object and then propose the angle of his next visit. The choice of the new direction is then based on the estimated angle and the defined rules. These rules specific to each type of mine are well defined for the case of mine and cylinder Rockan mine and also in the case of a general class mine. Performance evaluation of the method is evaluated by calculating two parameters: "rate of correct identification" and "false alarm rate" from the confusion

matrix. On the strategy using the predictive phase in the method presented, results are generally considered of high performance for both parameters calculated.

Generally, in order to show the contribution of the proposed method, classification approach is compared with classification on the same data, but using other strategies.

v. Conclusion

The focus of this paper is the study of the invariant approaches for sonar objects detection with application to high frequency sonar system images. This paper explained considerable recent work to underwater objects detection but also it presented a few of previous work in the same filed in order to establish the mutation of accurate method. Several research studies for detection approach turn to apply different methods of image processing including filtering, segmentation and objects' classification and involved, in the case of need, other technologies (principal component analysis, fusion methods, fuzzy estimation...). It is generally difficult to make comparison between different recognition algorithms, even for the same filed, since different test sets are used to evaluate performance. In fact, to validate the performance of each proposed algorithm, some works challenge to define a criterion that it considers robust to note the overall quality of the image. Other works make a comparison with previous results applied on the same sonar

Thanks to their diversity, many novel approaches are the result of a simple combination of two or more existing methods. However, more work is needed to understand a number of important factors which typically affect the sonar data.

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